International Journal of Disaster Risk Reduction 94 (2023) 103819

Contents lists available at ScienceDirect

International Journal of Disaster Risk Reduction

journal homepage: www.elsevier.com/locate/ijdrr

Data collection tools for post-disaster damage assessment of building and lifeline infrastructure systems

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A R T I C L E I N F O

Keywords:
damage assessment
Disaster data
Infrastructure systems
Lifelines
Post-disaster
Emergency response
Earthquake data
Hurricane response

A B S T R A C T

After a disaster event such as an earthquake or a hurricane, performing comprehensive and detailed damage assessment of lifeline infrastructure is critical to effective disaster response. In recent years, there has been a rapid increase in the implementation of varying tools for this purpose. These tools and resulting datasets include satellites, drone imagery, LIDAR scans, water level sensors, structural strain gages, etc. Each of these tools differs in terms of purpose, the precision of the data collected, and the resources required for data collection and processing. To this point, these technologies have been deployed in the field in an ad hoc and often uncoordinated manner. Coordinating data collection efforts has the opportunity to provide more detailed, accurate, and comprehensive lifeline damage assessment through augmenting datasets, validating information, and filling in information gaps. However, this requires a comprehensive understanding of available tools and their specific characteristics. This paper fills this gap by providing a critical and comprehensive review of the tools available for post-disaster damage assessment. This work focuses on the tools used to assess physical damage in lifeline networks and buildings. Included are tools across lifeline networks, including water, gas, transportation, power, and building infrastructure, as well as across hazard types, including earthquakes and inundations resulting from hurricanes or extensive rain. Each tool is presented and critically analyzed along key dimensions including coverage, precision, and availability over time to provide insights into integrating datasets across tools and identify gaps in existing data collection approaches. The results form the basis for recommendations for improving post-disaster damage assessment, including coordinated data collection, leveraging geographical interdependencies to assess buried infrastructure, and the inclusion of the detailed characteristics of the tool in the metadata. This work is the first to provide a systematic and comprehensive analysis of the tools for building and lifeline infrastructure damage assessment and provides a basis for future integration of datasets and development of post-disaster data collection tools.

1. Introduction

Following a disaster, carrying out a damage assessment on the major infrastructure systems is critical to defining the response needed [1]. For example, knowing the extent and degree of damage to specific assets is essential to know where and what type of resources to send and how recovery might proceed. However, determining the extent and details of damage is challenging, often requiring extensive time, labor, and financial resources to complete. This is especially true for civil infrastructure systems (e.g., roads,

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https://doi.org/10.1016/j.ijdrr.2023.103819
Received 18 November 2022; Received in revised form 20 June 2023; Accepted 21 June 2023
Available online 22 June 2023
2212-4209/

bridges, power networks, pipelines, buildings), which cover large geographical portions of a region and have complex system architectures. These networks are critical to the well-being and resilience of a community [2]. Understanding their state before, during, and after a disaster is, therefore, essential for effective emergency and disaster response.

To address this challenge, there has been an increase in the use of varying technologies and tools for data collection in the post-disaster damage assessment process. For instance, using satellite imagery in the first couple of days after a disaster has become increasingly widespread to establish a first estimation of infrastructure damage [3,4]. LIDAR scans [5,6], while visual inspection of damage data by an expert [7] has been used to assess damage on buildings. Social media information has also started to be utilized to locate damage for deploying personnel in rescue missions [8,9]. For example, Twitter data has been used to identify hotspots of damage by employing machine learning techniques to process the text in the tweets [10,11].

Even though more tools are available, there are still multiple uncertainties in the post-disaster damage assessment process due to lack of complete data and the involvement of multiple parties. With a lack of resources to cover all assets in widely distributed building and lifeline systems and the time needed to collect and process all the data, damage data is typically not complete, and it is unlikely to have reliable estimations across an entire affected area. In addition, the specific interests of multiple parties make this process more complex, with potential data collection repetition and poor data interoperability. For instance, emergency managers use satellite images in the first couple of days after a disaster for situational awareness, while researchers perform in-the-field reconnaissance two to three weeks after the event for specific academic purposes. While there is the opportunity to inform reconnaissance mission planning from the initial satellite imagery data, this information is usually not shared across parties, limiting the ability to leverage existing data sources to increase efficiency and effectiveness in subsequent data collection efforts. In practice, the available data collection technologies and tools are often deployed in an uncoordinated and ad hoc manner, each serving an entity's own specific interests. This disconnection results in communication problems, exacerbating the challenges associated with the data collection process [12]. It also inhibits the ability to perform coordinated data collection efforts that would result in more detailed, accurate, and comprehensive post-disaster damage assessment. To improve on this state requires the knowledge and understanding of the availability and capabilities of tools currently used in practice.

This paper provides a systematic and comprehensive analysis of the tools available and used for post-disaster building and lifeline infrastructure damage assessment. Having a complete understanding of damage assessment tools provides the basis for strategies to enhance the effectiveness of post-disaster damage assessment, including integrating datasets from across tools to assess damage across different building and lifeline systems and different types of damage, improving the workflow of entities involved in disaster response, and filling gaps in existing data collection approaches.

Past works on infrastructure damage assessment have focused on the types of damages in infrastructure and defining metrics for individual systems, e.g., a review of common damages to transportation networks and how to measure their performance [13]. Similarly, specific tools have been studied for damage assessment, such as remote sensing tools for earthquake building damage [14] or imaging technologies for underwater pipeline inspections [15]. On a larger scale, there have been studies on data sources broadly used in natural disaster events [16–18]. As of now, however, no paper has comprehensively and systematically evaluated the tools used for damage assessment of all major infrastructure systems as this paper seeks to do. With forces such as climate change expected to intensify the strength of natural hazards [19,20], the impacts of disasters on infrastructure systems will likely become increasingly severe. In this environment, it is critical to improve the effectiveness of post-disaster damage assessment. To do so requires a full understanding of the tools available for damage assessment and their characteristics, as presented in this paper, for improved use, coordination, and integration across data types.

The rest of the paper is organized as follows. Section 2 describes the methods for selecting the appropriate literature included in this comprehensive review. Then, Sections 3 to 7 provide detailed descriptions of the tools available for post-disaster infrastructure damage assessment for each of the examined five systems (water, gas, transportation, power, and building systems). Section 8 then discusses post-disaster data collection tools across different infrastructure systems. It discusses the scope of tools used in practice, evaluates and compares the tools available for each system, provides recommendations for integrating datasets across tools, identifies gaps in available data collection tools, and describes based on the results how to support more comprehensive lifeline damage assessment through coordinated post-disaster data collection. The paper ends with conclusion of the work in section 9 and a discussion of further work needed to improve the field of damage assessment on infrastructure systems.

2. Methods

The review process described in this section is developed with the purpose of presenting a comprehensive description and analysis of the current tools used in the field for assessing physical damage to infrastructure systems after an earthquake or a flood event has occurred. A tool in this paper refers to the physical mechanism, instrument, or technology used to quantify damage to an object. Five main types of infrastructure are studied: water, gas, transportation, power, and building systems. These five systems comprise the major lifelines and infrastructure systems for meeting essential community needs and are key drivers of economic recovery and development [21]. Not considered are airports, sewage networks, communication networks, and dams, among others. Even though these systems are also highly vulnerable to disasters [22], there is a lack of previous work in this area to include a detailed analysis of tools in this study. In addition, some of these systems behave similarly to those studied in this paper. For example, communication systems perform similarly to power systems, and their infrastructure is highly dependent on electricity from the power system [23], which is included in this paper. In addition, tools such as external pipe instrumentation and remote sensing techniques that are included for water infrastructure also apply to sewage systems.

Given the breadth of previous studies conducted on disasters and infrastructure systems, the articles included in this paper must follow certain guidelines to be included in the analysis. The main purpose of this paper is to catalog works that demonstrate the use of a tool for assessing damage in an infrastructure system after a disaster. Not included in this paper are research efforts not currently being used in practice, such as data fusion for damage assessment [24–26], which represent an important development for the future of the field but not the current state of tools available after a disaster. Thus, Table 1 describes the guidelines to include or exclude a work from the search process.

These guidelines make sure there is consistency when including articles for the review. With these guidelines, Fig. 1 depicts the search process to catalog the articles from the database used in this work. This systematic process, along with the guidelines presented in Table 1, follow the PRISMA protocol for conducting a consistent search process in a literature review [27]. The process starts with the sets of search terms used to build an online search. These sets include the damage-related words D, infrastructure system S, hazard H, and tool system T. Using the entire damage-related set and a combination of one term from each of the remaining sets, a single search command is built. For example, a possible combination would be *post-disaster damage assessment tool* and *damage quantification* of *water distribution systems* during *earthquakes* using *remote sensing*. This combination provides a specific command introduced in Google Scholar, generating a list of articles A that includes the set of keywords. For each article $a \in A$, the article is cataloged if it complies with the guidelines stipulated in Table 1. After finishing the article set A, a new search command is generated by changing one of the terms from the sets D, S, H, or T. In cases where the is no prior knowledge on the tool system, the term t is omitted from the search command. The search process finishes when all the combinations of command searches are studied.

After all the information about post-disaster tools is collected, the cataloging process consists of organizing the tools by the infrastructure system and hazard. As a result, each of Sections 3 to 7 includes three main subsections per infrastructure system: (i) a description of the types of damages in the system experienced after a disaster event and a broad description of tools available for that system; then detailed descriptions of the data collection tools available for each system organized by hazard type, including (ii) the tools used after an earthquake, and (iii) the tools used after water hazards (i.e., hurricanes and floods). The term water hazards joins these two disasters in the same category because the damage type and collection process face similar challenges in both cases, such as damage from inundation and inaccessible roads due to flooding. Even though some failure mechanisms might differ between these hazards (e.g., damages from storm surge or winds), using a single category avoids the duplication of tools in the analysis.

In addition to detailing the tools for each infrastructure system, using the information collected from all the articles on post-disaster tools, a series of analyses is conducted to study the distribution of tools across infrastructure systems, compare the coverage and precision of the tools, identify gaps in damage assessment, and discuss leveraging geographical interdependencies to improve the damage assessment of buried infrastructure. These analyses comprise Section 8.

3. Water supply networks

Water distribution systems are critical for maintaining population health and safety. These networks are highly vulnerable to natural hazards, where disaster events can destroy infrastructure assets (e.g., pipelines) and disrupt service delivery. Multiple components make this system highly complex, with the need for supplying, processing, and distributing water to fulfill high-quality standards over large service areas. The water system components vary in number, type, geographic distribution, physical characteristics, and management approach. The disruption of any of the system components results in a reduction of access to services. Such disruptions can have critical health impacts, leading to increased social and economic impacts of the disaster on a community. However, the main components for water distribution are pipeline networks. Accordingly, varying tools are available to assess damage in these components, as described in the following sections. A review of the impacts of damage on water infrastructure, including the effects on health, education, environment, and culture, can be found in World Bank (2017b). The World Health Organization states that for water infrastructure, it is "imperative that, after events, lessons are learned, including what did not go well and should be improved" (World Health Organization & Regional Office for Europe, 2011). Such studies highlight the need for effective data tools to assess the damage in water distribution systems after a disaster.

3.1. Damage assessment from earthquakes

Among the components comprising water distribution networks, pipelines are the most prevalent, leading to possible widespread damages after earthquakes [28]. The damage comes from two main sources: ground shaking and liquefaction-induced permanent deformation. Water pipelines are mostly buried and have large differences in materials and sizes, along with high variability in site

Table 1
Guidelines used for cataloging articles in the review.

Guidelines for including an article:
- Article references the use of a tool for identifying damage
- Tool has been previously used in the field after a disaster
- Article describes the type of damage to a specific infrastructure system

Guidelines for excluding an article:
- Its purpose is to analyze post-disaster data but does not describe a tool
- Tool is used for pre-disaster damage analysis (disaster mitigation, predictive scenarios)
- It discusses the damage after a disaster but not how it was assessed
- Article describes damage metrics on infrastructure systems but not the tools to measure damage
- Article includes tools for measuring losses of different systems (casualties, economic impacts)

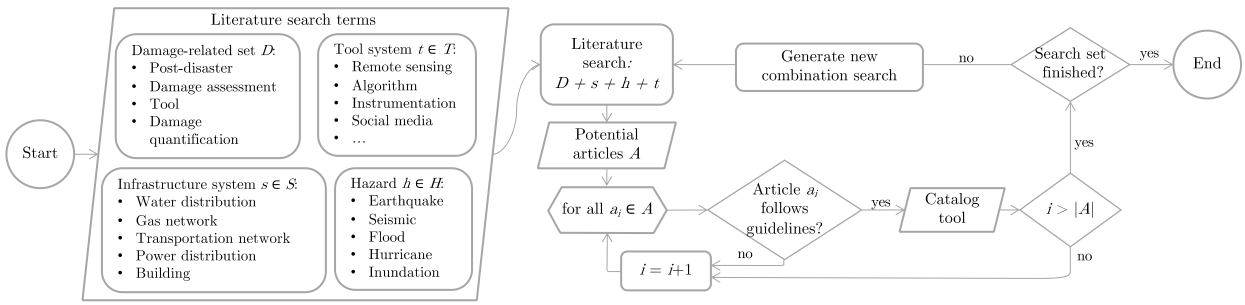

Fig. 1. Search process for cataloging articles in the review.

conditions. Given these differences and configurations, damage to water infrastructure from earthquakes is measured by pipe damage rate (also quantified as repairs per unit length), which is affected by the ground shaking intensity, pipe material, pipe joint, and pipe diameter [29]. This metric has been used because it allows for comparisons of the damage extent in water networks between regions [30]. The most common method to assess this damage is by performing field inspections, where a wheeled platform with closed-circuit television (CCTV) is mounted on the inside of a pipe to find blockages, cracks, or joint issues.

Another way to assess damage is by placing pressure sensors on the pipes. However, these sensors do not give the precise location of the failure, and thus field inspections are still required. Recent works have dealt with this problem by building a sensor network for monitoring water pipes to improve the ability to detect and localize damage in the water distribution network [31]. Advanced Metering Infrastructure (AMI) systems also address this issue by creating a multi-sensor network to measure not only pressure but also turbidity, temperature, and conductivity [32,33]. Other technologies for inspection include infrared, microwave, optical, and ultrasonic-based sensors [34,35]. The main advantage of AMI multi-sensor networks compared to vehicle-mounted cameras using CCTV is in the inspection time. Sensor networks provide real-time data on the state of a pipeline, compared to the need to mount and deploy a robot in the pipeline to look for major damages. However, sensor networks require an initial investment to be implemented before the disaster occurs and many sensors to be placed throughout the network for them to be effective in finding damage locations.

Given the cost of collecting post-earthquake damage data on water pipeline networks, ground motion parameters can be used estimate damage through correlations between disaster event intensity and pipeline damage by identifying locations with the highest ground displacements [36–39]. These correlations depend on multiple variables such as peak ground velocity (PGV), peak ground acceleration (PGA), and maximum ground strain (ε_g). Among these, studies have found that PGV is a better predictor of pipeline damage than PGA as PGV is related to ground displacement, the main cause of seismic pipeline damage [36].

Historical data on water pipeline damage from earthquakes can be found in Ref. [28] who provide a review of pipeline damage datasets from major earthquakes such as: the Northridge earthquake (Jeon & O'Rourke, 2005), the 2007 Niigata Chuetsu-Oki earthquake in Japan [40], and the 2011 Christchurch earthquake in New Zealand [41].

3.2. *Damage assessment from water hazards*

After an inundation occurs, several components of water networks can be damaged, including meters, regulators, valves, pumps, manhole covers, hydrants, and electrical panels. Much of this damage comes from ground subsidence and loss of bedding. This results from the supersaturation of soils, which causes the supporting soil to shrink and subside. In water hazard events, damage can occur not only during the event itself but also in the response stage, when heavy trucks and equipment used to remove debris can break shallow buried service pipes [42].

In the case of flooding and inundation events, remotely operated vehicles (ROVs) have been used to perform underwater inspections of pipelines. The primary purpose of using unmanned vehicles is to avoid dewatering a site entirely, or in case dewatering is required, to minimize the disruption by gaining as much information as possible about pipeline conditions [43]. Other technologies used for data collection include sub-bottom profilers that have been used to generate images of sediment stratifications, bedrock, and

Table 2
Summary of tools for damage assessment of water infrastructure.

Tool	Description
Closed circuit television (CCTV) inspections	Unmanned cameras are used to inspect damages within pipelines.
Ground displacement data	Ground displacement is correlated with pipeline damage using PGA, PGV, and ground strain.
Pressure sensor	Low pressure is correlated with damage near the location of the sensor. However, the location of failure is not precise.
Multi-sensor network	Sensors, including Advanced Metering Infrastructure, measure pressure, turbidity, temperature, and conductivity to estimate damages in the network.
Remotely operated vehicles (ROV)	ROVs are used to perform underwater pipeline inspection. These inspections can occur inside or outside the pipeline.
Sub-bottom profilers	Profilers are used to develop images of sediment stratifications, bedrock, and objects such as buried pipelines.
Synthetic Aperture Radar (SAR) sensors	Satellite imagery is coupled with computer vision algorithms to estimate flooded areas and resultant pipeline damage.

objects such as buried pipelines using either a digital or paper recording device [44]. However, their primary limitation is acoustic interference, which results in sub-bottom images that are more difficult to interpret [15]. Researchers have also incorporated satellite data and image processing to provide insight into pipeline damage and improve flood monitoring for inferences on pipeline conditions [45]. More specifically, Synthetic Aperture Radar (SAR) sensors have been used to identify flooded areas in rural environments, which are intersected with the pipeline network locations to estimate their damage [46].

Finally, several standards and guidelines exist for post-disaster assessment of water distribution infrastructure. The U.S. Pipeline and Hazardous Materials Safety Administration (PHMSA) requires inspections of pipeline infrastructure following extreme weather events. Multiple PHMSA Advisory reports have been published, including ADB 2015–02 (Potential for Damage to Pipeline Facilities Caused by the Passage of Hurricanes) and ADB-2016-01 (Potential for Damage to Pipeline Facilities Caused by Flooding, River Scour, and River Channel Migration) [15]. ASCE has also published a guide on integrity inspections called the *Standard Practice Manual 101 – Underwater Investigations*. This includes a series of inspections of pipelines needed after floods and hurricanes [47]. A summary of the data collection tools available to assess damage to water infrastructure is provided in Table 2.

4. Gas networks

Damages to gas networks can occur as a result of a range of events, including natural hazards such as earthquakes or floods, temperature changes, or terrorist attacks [48,49]. As a result, these systems are heavily instrumented, with multiple techniques used for pipeline maintenance. This instrumentation has migrated to post-disaster damage assessment, where damage typically occurs as pipeline failures. Damages to natural gas pipelines after a natural disaster are particularly important to detect as they can lead to cascading disasters such as fires after earthquakes. However, papers that study tools developed specifically for post-disaster damage assessment of gas pipelines are scarce.

The tools used to assess the state of gas networks fall into three categories: internal sensing, external sensing, and remote sensing. While initially implemented for varying purposes other than use in post-disaster contexts (such as to conduct routine maintenance inspections), these tools can be used for post-disaster damage assessment. Tools for internal sensing require instrumentation that goes underground and within the pipe to search for pipeline failure. External sensing tools are mounted on the surface of the pipe and are used to measure displacements. Remote sensing includes the monitoring of physical characteristics using overground measures.

4.1. Damage assessment from earthquakes

In terms of disaster damage, there have been multiple studies of the damages to gas networks from earthquakes. Seismic events generate different types of ground failures such as landslides, liquefaction, and permanent ground deformations. Gas pipelines are highly vulnerable to these failure types, especially in earthquakes with a Modified Mercalli Intensity (MMI) higher than VIII [50]. The damage types arising from permanent ground deformation in gas steel pipes can be found in Ref. [51]. Studies from previous earthquake damage show that damage in pipelines predominantly occurs at the welds, and regardless of age, the pipe between welds performs well [50]. To detect these damages, data from past earthquakes has been useful to perform pipeline damage assessment based on correlations with earthquake intensity parameters. A study from the Chi-Chi Earthquake in Taiwan showed that Arias Intensity (AI) correlates well with the seismic vulnerability of gas pipelines [52].

An example of internal sensing tools that have been used for gas pipeline networks are intelligent PIG (pipeline inspection gauge) devices. These instruments, although first implemented as cleaning devices, have been modified to inspect pipeline damage using sensors including eddy current and ultrasonic transducers [53]. Given the size of gas networks and the amount of data produced by all these sensors [54], proposed a multidimensional big data processing tool to improve the precision of smart PIG tools. A comprehensive review of ultrasonic tools for pipeline damage detection can be found in Ref. [55]. Internal pipe sensing has been used for pipeline inspection after earthquakes, including Magnetic Flux Leakage (MFL) and Pressure Point Analysis (PPA). First, MFL is a tool that senses a higher flux density or magnetic field in the pipeline to correlate it with damage [56]. This is the most common method implemented in PIG devices, which are used for inspecting pressurized pipelines. It is used for gas pipelines since the method can only be used in pipe systems made of steel or cast iron [57]. Second, in PPA, pressure sensors are used to quantify leak rate and pressure drop given a crack or damage to a pipe [58]. This tool is useful to determine the presence of a leak but cannot determine the exact location of damage [59, 60]. At a large scale, pressure sensors can be implemented using large-area electronics (LAE) and sparsely spaced sensors at a relatively low cost [61]. However, main challenges with this approach are in providing a long-term power supply and durability [62,63].

External methods have also been implemented for pipe damage assessment, especially in regions with non-instrumented pipes. The most common methods are fiber optic cables and acoustic detectors. Fiber optic cables are buried sensors that follow the same path of the gas pipeline and measure changes in the temperature with high precision over several tens of kilometers [64]. These cables can localize damage within a meter spatial resolution and transmit data over long distances, making them useful for leakage monitoring [57,65]. However, such fiber optic cables need to be installed prior to the disaster and require additional upfront investment with deployment most common during initial construction of the gas pipeline. Acoustic leak detectors assess damage to pipelines by locating strong acoustic emissions that result from pipe leakages [66]. These sensors are applied externally using steel rods, which conduct the sound to a sensor mounted on the rod. The precision of this method and the ability to accurately assess damage depend on the interval length between rods, making it an accurate option with the downside of requiring several sensors for long pipes [59].

Finally, remote sensing tools have been used to assess damage in gas pipelines. These sensing techniques include the use of electromagnetic waves to probe a few meters underground, providing images that indicate pipe failures at the subsurface level [67]. Infrared (IR) cameras have also been used to determine damage in pipes by converting heat energy emitted from the pipe to reveal defects [55,68]. This process is known as computerized IR thermography and is suitable for gas pipeline inspection because it is a rapid non-destructive test, which can be performed without interruption of service [57]. Included in remote tools are helicopter inspections, which utilize IR laser remote sensing to look for damages in pipelines [69]. This type of inspection is continuing to evolve with the use of UAVs, by combining lasers and electro-optical sensors to locate gas leaks [70]. This method, however, is still in development and only works for unburied gas pipelines.

Note that all the tools described in this section have been mostly used for maintenance and monitoring purposes. They do, however, have applications in gas pipeline damage assessment with promising capabilities to leverage for post-disaster damage assessment.

4.2. Damage assessment from water hazards

Given the underground nature of gas pipeline networks, water hazards (i.e., hurricanes and floods) have more indirect impacts on these systems. Damage to gas networks due to water hazards is due to ground deformations from soil saturation and subsidence [42]. Although less prominent than ground failures from earthquakes, pipeline damage resulting from floods can be measured using many of the same tools described in the previous section to detect pipeline failures after earthquakes. Table 3 summarizes the tools available for use in damage assessment of gas infrastructure.

5. Transportation networks

In the aftermath of a disaster, the connectivity provided by road networks is critical to facilitate survivor evacuations; support rescue operations; and effectively transport crews, goods, and materials to repair and recover other infrastructure systems [71]. However, achieving high connectivity after a disaster is challenging, given that roads and bridges are vulnerable to multiple hazards. They are affected not only by geotechnical failures (e.g., landslides and ground displacements) but also by structural failures (e.g., bridge failures and disruption by debris accumulation).

In terms of data collection tools for damage assessment of transportation systems–as with building infrastructure as will be discussed in a following section–their exposure to the earth's surface means that the data collection process benefits from the use of remote sensing tools such as unmanned air vehicles (UAVs) and satellite images. This increases the number of data tools that can be used in the aftermath of a disaster compared to the buried pipelines of water and gas infrastructure previously described, increasing the range of damage that can be assessed and decreasing the uncertainty in the assessment of the damage with increased available data sources estimating the damage.

5.1. Damage assessment from earthquakes

Earthquakes can cause severe damage to both roads and bridges as part of the transportation network. Ground movements lead to road cracking due to slope failure beneath the carriageway, and vertical or horizontal displacements in the pavement due to fault rupture. Road damage can be estimated based on hazard level (e.g., earthquake intensity), exposure (e.g., distance from epicenter), and network functionality (e.g., road is open or closed) [72]. Multiple other inspection and remote sensing tools are available to directly detect physical damages in transportation networks.

Visual assessments from helicopters or by road, if conditions permit, provide entities with the ability to assess road damage across larger areas, including assessments in isolated areas [73]. These inspections help to provide pathways for delivery of essential supplies and to evacuate people from the most vulnerable regions. However, visual inspection from helicopters can be too costly for all communities. Therefore, one of the main emerging types of tools to assess damage in the road network is through remote sensing approaches. Remote sensing denotes collecting information from a distance using tools such as satellite images and UAVs [74,75]. From these tools, satellite images are the most common in the literature. Several authors have used pre- and post-earthquake images to identify road damage from earthquake-induced events such as landslides, debris accumulation, and fault ruptures [76–79]. These tools can provide high-resolution information and high coverage over distributed geographical areas with a relatively short implementation time. However, extra analysis is needed for some specific types of damages, including landslides, where it may take months to post-process the data to get detailed locations of slope failures (Hughes et al., 2019). Light detection and ranging (LIDAR) sensors have also been used to measure road deformations after a disaster. In practice, LIDAR provides imagery information with less coverage,

Table 3
Summary of tools for damage assessment of gas infrastructure.

Tool	Description
PIG device	Pipeline inspection gauges (PIGs) are intended to be run in an operating pipeline to find several types of damages in pipelines (e.g., dents, loss of coating, cracks, metal loss defects).
Ground motion data	Permanent ground deformation correlates well with pipeline damage.
Arias Intensity	A measure of earthquake intensity used to estimate pipeline damage.
Magnetic Flux Leakage (MFL	A measure of higher flux density or magnetic field in the pipeline that correlates with damage.
Pressure point Analysis (PPA)	Pressure sensors that quantify leak rate and pressure drops given a pipe crack or damage.
Fiber optic sensors	These tools include point sensors, long-gauge sensors, and distributed sensors. Structural health monitoring is the primary use of these tools.
Acoustic leak detectors	Acoustic sensors assess damage by locating strong acoustic emissions resulting from pipe leakages.
Electromagnetic sensors	Electromagnetic waves penetrate underground, providing images that indicate pipe failures at the subsurface level.
Infrared (IR) cameras	IR thermography is used to determine damage in pipes by converting heat energy emitted from the pipe to reveal defects.
Helicopter inspection	IR laser remote sensing measures damage in unburied pipelines.

given the sensor range, compared to satellite images, but at a much higher resolution. After the 2010 Maule Earthquake in Chile, for example, reconnaissance teams used LIDAR sensors to visualize 3D models of multiple road failures [80].

Beyond roads, ground motions also greatly impact transportation network components such as bridges. These critical structures can be highly vulnerable to ground motion shaking during earthquake events and experience potential structural failures. Therefore, in recent decades, the use of instrumentation on these structures has increased, with expanding use of sensors and data analysis for structural health monitoring applications [81–83]. These sensors provide real-time data about structural components, including accelerations, strains, and displacements, to locate damage and estimate structural serviceability. As the size and cost of these sensors decrease, multiple sensors can be deployed over one structure. Data from these sensors have been used to estimate bridge damage, often coupled with high-fidelity structural models to conduct static and dynamic analyses [84,85]. Strain sensors have been used to estimate bridge damage states based on displacements. Bassam et al. for example, monitored bridge pier deformations using fiber optic Bragg grating sensors (FBG) to estimate the bridge damage state [86]. Fiber optic sensors are relatively easy to install and can provide high-resolution data with a high signal-to-noise ratio [87].

Other tools can be used to assess the damage if there is no instrumentation in the bridge. For instance, LIDAR sensors have been used to assess deformations in bridges [88]. This technology is particularly useful for bridges given that it generates quantitative measures of the damage at a high resolution for a given asset and can be done after the disaster event occurs. However, the success of this method depends on the equipment, access, and time availability to scan the bridge after the event. Another critical component of the post-earthquake performance of a bridge is its foundation. Researchers have developed methods to assess the seismic performance of bridges under varying soil conditions [89] and used correlations to estimate the damage to underground piles by measuring the maximum column drift ratio and the surface displacement [90]. Bridge displacements can be measured using surveying tools such as LIDAR, conventional surveying tools, or computer vision [91,92]. Rotation measures in affected components are also used to estimate damage [93]. These are measured using micro-electro-mechanical systems (MEMS) accelerometers, which quantify DC (zero frequency) accelerations to measure the relative acceleration to the direction of gravity using the acceleration on each axis of the sensor [94].

Finally, given the dependence of the performance of road networks on their geotechnical foundations, varying research associations have focused on collecting geotechnical data for post-disaster transportation network assessment. One of these entities is the Geotechnical Extreme Events Reconnaissance (GEER) Association, which conducts detailed reconnaissance missions and documents observations of perishable post-disaster information practice [95]. From this perspective, there are current efforts to improve the effectiveness of the tools used to assess road damage. For instance, Seidy and Rastiveis developed a deep learning framework to speed up the time to process LIDAR data from roads [96]. Another type of innovation involves wireless sensor networks, using low-cost sensors to collect real-time dynamic data about road availability post-disaster [97]; X.-G. Sun, He et al., 2011). For example, road availability is measured using a combination of ground motion and sound sensors to send warning messages to a command center in case a landslide is detected [98].

5.2. *Damage assessment from water hazards*

In consideration of the potential damage to transportation networks due to water hazards, multiple types of damage and impacts have been observed. Road networks in coastal regions are highly vulnerable to floods, hurricanes, and tsunamis, given their proximity to ground level and poor ability to permeate water [99]. High inundation depths result in road closures, which are difficult to recover in a short time due to the inability to evacuate high volumes of water. Even though transportation demands change significantly after a disaster during the emergency response phase of an event [100], there is still a high impact to the connectivity of the network and users' travel time. For instance, Pregnolato et al. quantified the change in vehicle velocity per water depth of inundation [101]. Gori et al. studied roadway accessibility to support response services for vulnerable populations [102]. Road damage and closures also occur caused by the failure of geotechnical structures such as landslides. These failures are a result of reduced soil strength due to heavy rainfall, which increases pore pressures and decreases the effective stresses in the foundations and slopes [103]. It is important to note that not all road damage is evident after the disaster. In cases of long-term flooding, water may seep through porosities in the pavement surface and erode the base and sub-base of the road, leading to subsidence that may cause serious accidents over time [104].

In order to assess these types of road damages, remote sensing is the most common tool used in practice. The tools available are similar to those used in post-earthquake damage assessment. The data collected on landslides, for example, are useful for both post-earthquake and post-storm damage assessment of transportation infrastructure. More specifically for water hazards, high resolution satellite images have been used to identify different infrastructure lifelines (including roads) and classify damage after hurricanes [79,105]. At a higher resolution but lower coverage, LIDAR images were collected with airborne systems to capture flood zones in a neighborhood of New Orleans after Hurricane Katrina in 2005 [106]. These images were post-processed to identify road blockages and quantify the increase in travel time due to the network failure. While the tools so far described have been used to identify flooded roads after hurricanes or rain events, they cannot determine the water depth at a specific location. The level of damage is correlated with the amount of inundation [101]. For this purpose, water level gauges can be rapidly installed before a storm to quantify water depth at specific locations with high precision [107]. The use of sensor networks to measure real-time water levels are increasing in popularity [108,109], and sensors can be mounted on bridges or near rivers to rapidly estimate water depth in case of flood events.

Given the ease and accessibility for public users to identify damage in overground transportation infrastructure, another vital source of information for estimating the damage impacts of water hazards such as storms and hurricanes is social media data. Twitter images provide an effective way to locate damage immediately after the disaster. Even at a low resolution and with approximate locations, emergency managers can use this information to identify high-damage regions, deploy response teams, and prioritize locations for collecting data with remote sensing or other tools at a higher resolution. Cervone et al. presented a methodology to include

Table 4
Summary of tools for damage assessment of transportation networks.

Tool	Description
Helicopter reconnaissance	Used for rapid assessment of major damage to roads.
Optical imagery from satellite	Used to compare pre- and post-disaster images to find road closures due to landslides and ground failures.
LIDAR sensor	Generates point clouds to measure ground deformations or element displacements at high resolution. Processing this data usually requires high computing power.
Bridge strain gauge	Used for estimating deformations in critical components of a bridge. This data can be coupled with computer models to better estimate the damage state of the bridge.
MEMS accelerometer	Quantifies rotations in bridge components to determine drift ratios.
High resolution camera on bridge	Used to measure pier deformation and other structural component displacements.
Fiber optic array on bridge	Used to measure pier deformation and other structural component displacements.
Social media data	Texts and images from multiple platforms (e.g., Twitter, Reddit, Facebook) are used to identify damages in the aftermath of a disaster. Social media data is useful to identify hotspots of damage.
Field inspection	Field surveys are done to better assess specific damages to bridge structures and roads including soil and pavement failures.

Twitter images to identify ‘hot spots’ and to task remote-sensing data collection for the 2013 Boulder floods [110]. Dashti et al. used the same case scenario to classify road damage with Tweet images, increasing the precision of the damage assessment for disaster response [111]. Tien et al. focused on processing the text in Twitter data to identify damage in transportation infrastructure [112].

In terms of bridge vulnerability, water hazards generate high impacts from multiple sources, including storm surge, wind, debris, scour, heavy rainfall, and water inundation. An event such as hurricane Katrina resulted in a wide range of damage to these structures. A detailed description of the damages and failure types from this event can be found in Ref. [113]. The GEER Association has also performed reconnaissance tasks after major hurricanes. For instance, after Hurricane Maria passed through Puerto Rico in 2017, the team inspected some of the affected bridges, recording their coordinates and providing images of damage [114]. The data collection process for these structures is usually done through individual bridge inspections in the field, requiring significant personnel and time resources. To determine some of the damage locations before performing these field inspections, reconnaissance teams use satellite images taken days after the event. Thus, together with the subsequent field investigations, the total data collection process can take days or weeks to implement to collect detailed damage data over broad areas. Table 4 summarizes the tools available for use in damage assessment of transportation networks.

6. Power networks

Power supply networks are complex systems that are critical to provide electricity to a community after a disaster and support multiple interdependent infrastructure systems such as water treatment plants, pump stations, communications networks, etc. Maintaining reliable service during and after a disaster is essential for emergency management and response capabilities. Power networks have multiple components that provide redundancy and resilience to the system when part of it fails. Among these components, substations, transmission lines, and distribution lines are the failures responsible for most outages [19]. In terms of individual component failures, note that this section does not focus on structural failures in, for example, maintenance buildings or operations buildings, as Section 6 addresses building infrastructure damage. For the other elements of the power system, to quantify the damages in these critical components, most publicly available data are based on service disruptions such as outage areas and downtime. These metrics give an overview of the damage, but not a specific identification of the component damage in the system. For instance, a power outage in an area can result from a failure in a distribution line or substation. Information about damaged components is usually protected by utility providers, making it difficult to use data about power network damage in other post-disaster damage assessments.

6.1. *Damage assessment from earthquakes*

Compared to other lifeline systems, the distribution network in power systems tends to perform relatively well after an earthquake. This is because of the built-in resilience of the system in being able to reroute power to minimize power loss in a region after an outage [115]. Even so, transmission and distribution lines are vulnerable to ground motions and liquefaction during seismic events [116,117]. Of these components, transmission lines are more robust than distribution lines. The former typically consists of truss or lattice designs that support the conductors, while the latter are based on poles, mostly made of wood. In some cases, distribution lines are buried. While buried lines are more resilient to water hazards, as will be discussed in the following section, they can be more vulnerable during earthquake events due to liquefaction compared to overhead structures. As was found by field inspections following the 2010–2011 Christchurch, New Zealand earthquakes, nearly all buried cable failures occurred in areas where there was observed liquefaction and not necessarily high ground shaking [118].

Currently, there is no wide implementation of sensors outside of smart grid-related operations to assess damage to components. With a lack of publicly available data about specific damages to components in the system, most power distribution network damage is measured indirectly as outages to specific populations. Damage data for power networks typically relates to community effects after a disaster with a focus on functional impact (e.g., affected customers and outage areas). For instance, damage to electric power was cataloged in terms of affected users after three earthquakes: the 1989 Loma Prieta, 1994 Northridge, and 1995 Hyogoken-Nanbu [119]. [120] did assess component-level damage from earthquakes. However, the focus was on damages to power supply rather than distribution components (i.e., high-voltage electric substation equipment) from recent earthquakes in Japan, New Zealand, the

US, Chile, China, and Haiti.

In recent years, utility providers have increased the implementation of Advanced Metering Infrastructure (AMI), a collection of communication systems to enhance the assessment of electrical grids in real time [121]. This tool was initially developed for demand allocation of power and has expanded in use with the development of the smart grid. However, it can ultimately be used for effective damage assessment of outage areas [122]. Increasing instrumentation in power systems will lead to an enhanced post-disaster damage assessment. However, this data must be available and shareable among entities for it to be useful for emergency and disaster response.

6.2. Damage assessment from water hazards

Hurricanes and floods generate multiple damages in power systems, not only because of the diversity of components of the network but also due to the variety of hazards experienced during these events. Severe wind speeds, storm surges, inundations, and precipitation all play a major role in the impact on power networks. For example, overhead lines are vulnerable to hurricane winds and carried debris. The vulnerability of electric lines to water makes them susceptible to damage in floods. Substations are also vulnerable to floods and cyclones. Tall components of electrical substations are susceptible to damage from wind, and floods can damage critical components that lead to major service interruptions [19]. Even though power demand can be satisfied by rerouting electricity [123], the connectivity of the network makes it fragile against cascading failures. This is why cases with less than 1% of damage in the network could affect all electricity users in a county [124].

Field inspections have provided much of the available damage data for power networks, including after recent hurricane events. For example, field inspections showed that Hurricane Maria in 2017 generated power outages over the entire island of Puerto Rico that lasted for ten months. One of the reasons for this extended outage was the failure of multiple transmission lines located in mountainous terrain, which complicated the repair process [125]. Field inspections have also been recorded for Hurricanes Isaac [126], Rita [127], Katrina [128], and Sandy [124], where heavy flooding was a major contributor to system damages.

Remote sensing data from drones and UAVs have also been used to capture power disruption information [129]. These devices collect higher-resolution data at the expense of broad data coverage and high post-processing time. However, using them requires good weather (i.e., no strong winds or rain) to fly the devices properly. During the response stage, flight paths have been created to minimize operating costs and maximize coverage for power network damage assessment [130].

In addition to these remote sensing tools, which have also been used to assess damage in other civil infrastructure networks, power systems have another key feature that differentiates them from other lifelines. This is its use to provide lighting for communities, and thus the opportunity to infer and identify outage areas at night from the lack of light in buildings and streets. Compared to other networks, these outage areas can be determined with higher precision using remote sensing tools with less complex computer vision algorithms needed to assess damage. Starting with Hurricane Maria in 2017, NASA developed a satellite-derived Nighttime Lights (NTL) product to capture the radiance in a region pre- and post-disaster. By comparing the satellite images released every day starting a week after the event, it was possible to assess the power downtime in different regions of Puerto Rico [131,132]. This is done with the Visible Infrared Imaging Radiometer Suite (VIIRS) Day/Night Band (DNB) onboard the NASA/National Oceanic and Atmospheric Administration (NOAA) Suomi National Polar-orbiting Partnership (Suomi NPP) satellite [133]. The limitation of this tool is that it relies on having clear skies to assess the region's light; thus, cloudy days following a hurricane makes data collection challenging [134].

Finally, social media data has also proven helpful in determining power outages after flood events. For instance, it is possible to collect both geo-tagged and non-geo-tagged tweets to identify affected areas. For this purpose, Tien et al. developed a text-filtering approach [112], Mao et al. proposed a deep learning-based framework [135], and Paul et al. used Latent Dirichlet Allocation algorithms along with transfer learning models [136] to detect power outages. Twitter data has also been coupled with data from remote sensing tools, where geo-tagged tweets have been used to enhance the resolution of satellite images by using a spatial interpolation [137]. The combination of machine learning techniques and social media data is more useful during the situational awareness stage (first days after the event) when detailed data is less widely available. Section 7 will expand on the need for more frameworks that combine information from multiple types of post-disaster datasets to increase awareness of damage to lifelines across a community. Table 5 summarizes the tools available for use in damage assessment of power infrastructure.

Table 5
Summary of tools for damage assessment of power networks.

Tool	Description
Satellite imagery	Used to identify overground damages to transmission lines. Also, there is a correlation between liquefaction zones and underground failures of power lines, which can be determined with these images.
Field inspections	Used widely in post-disaster damage assessment of power networks.
Functional impact data	Information about impacted areas with loss of power are used to estimate damages in power transmission and distribution lines.
Advanced Metering Infrastructure (AMI)	Real time communication systems currently used for demand allocation. However, they have been started to be implemented for damage assessment.
Visible Infrared Imaging Radiometer Suite (VIIRS)	Mounted on satellites, these sensors capture Nighttime Lights (NTL) to assess power outages by comparing pre- and post-event data.
Unmanned aerial vehicles (UAV)	Used to capture high resolution imagery data for damage assessment.
Social media	Geo-tagged tweets are used to identify affected areas using computer vision or natural language processing algorithms.

7. Building infrastructure

Among the systems analyzed, the building infrastructure has the most diverse set of data tools and equipment available for post-disaster damage assessment. Many researchers and companies are involved in the process of collecting data to both assess damage and identify the causes of structural failures. The types of damage that can be expected from these structures are quite diverse, with structures of different materials, design, and age having varying damage types and failure mechanisms. For example, wooden houses, concrete buildings, or steel storage structures will exhibit different types of damage due to earthquake or hurricane events. This section focuses on the data tools used to measure different types of damage and provides an overview of the methodologies used to assess the extent of the damage at different scales. Note that the scope of this paper does not include damage prediction data.

7.1. Damage assessment from earthquakes

In an earthquake, building infrastructure is one of the systems most prone to failure, given its vulnerability to lateral movement. Impacts range from small cracks to total collapse of buildings. Since these structures vary considerably in age, material, and complexity, it is difficult to standardize damage assessment for all of them. Okada and Takai developed a description of the types and damage patterns found on buildings after an earthquake [138]. The variety of damages also leads to a diverse set of tools available to measure damage on buildings.

Given widespread instrumentation for measuring earthquake intensity parameters and the relation between these parameters and building damage, several methods exist for assessing building infrastructure damage based on earthquake parameters. The most common data used in this way is the moment magnitude. This measure of intensity can give a preliminary estimate of the expected damages in a region. In most cases, the greater the magnitude, the greater the expected damage [139]. The moment magnitude and corresponding peak ground acceleration (PGA) are used in the damage assessment process as an indirect measure of the level of damage in a region. For example, the Thiel-Zsutty method (TZ method) uses the PGA and some building-specific parameters (related to vulnerability and soil type) to estimate the damage ratio after an earthquake [140,141]. The method estimates damage before reconnaissance teams can collect field data about specific damages on each building. At a larger scale and with the increase of earthquake instrumentation in multiple countries, it is now possible to generate maps with the acceleration profile of an earthquake showing the attenuation of the PGA from the epicenter. One of these maps is the ShakeMap, which is produced and published by the US Geological Survey (USGS) minutes after the event [142], and can be used to infer building damage in a region [143].

Another source of information used to estimate damage in the early stages of the disaster is data from remote sensing tools. Specifically, for earthquakes, high-resolution satellite images are taken by several entities such as NASA, USGS's Landsat, NASA's Moderate Resolution Imaging Spectroradiometer (MODIS), and the European Space Agency's Sentinel-2. The USFederal Emergency Management Agency (FEMA) uses these images for preliminary damage assessment, which forms the basis for releasing federal funds to local governments after a Presidential disaster declaration is approved (FEMA, 2020). In addition to optical imagery, other intensity measures are also collected. For example, the Synthetic Aperture Radar (SAR) satellite generates an energy signal to measure the amount that is reflected from Earth [144]. NASA's Jet Propulsion Lab uses this satellite to compare pre- and post-disaster images and generate a Damage Proxy Map with estimations of regions with high damage [4]. This product has been widely used in recent years to obtain a first estimation of damage in a region. SAR data and optical imagery have also been used to estimate other damage parameters such as debris accumulation and physical exposure [145–150]. [14] provide an in-depth review of remote sensing for building damage detection.

A couple of days after the disaster, local emergency managers deploy expert teams to assess individual damages to structures. For instance, FEMA guidelines include building damage classifications into one of four categories: affected, minor, major, and destroyed [151]. In this case, data collection is conducted by personnel gathering data in the field about individual buildings. Such data collection processes require personnel training pre-event regarding reconnaissance data collection and the deployment of significant human resources for data collection. In addition, the dependence on individual personnel and often subjective judgments on assigning damage levels leaves the process open to variability across personnel. Potential biases and uncertainties result in determining the extent of damages depending on the individuals and level of training. However, field inspections can provide detailed information on damage severity and specific damage characteristics that may be otherwise difficult to ascertain at the individual building level.

In addition to these building surveys, varying entities collect data related to building damage assessment for forensic engineering purposes. For significant earthquake events, researchers are particularly interested in the cause of severe building damages, including collapse. These engineers arrive after the main emergency response stage to avoid potentially interfering with response efforts. The Earthquake Engineering Research Institute (EERI) oversees one of the largest programs to gain insights from earthquake events, including through Learning From Earthquakes program, which has been running since the Venezuela Earthquake in 1967 [152,153]. This program includes coordinating international reconnaissance teams and a virtual analysis of damage done through the Virtual Earthquake Reconnaissance Team before deploying people to the field [154].

Varying technologies are available to assist reconnaissance teams. Some of these tools include remote sensing technologies, but at a finer scale than the previously described satellite imagery, which are used to improve the damage assessment on structures. LIDAR sensors provide data at high resolution to measure deformations in affected structures [5,155]. These sensors can also produce a point cloud to generate a 3D model of the structure. Unmanned Aerial Vehicles (UAVs) equipped with LIDAR sensors are also used to assess damage at a larger scale with a lower resolution [6,156,157]. These tools are useful to support rapid damage state estimation of multiple buildings in less time, e.g., using a single UAV flight. The distance between the sensor (i.e., UAV or drone) and the subject (i.e., the building) impacts the resolution of the information that can be collected.

However, collecting such imagery data is not sufficient to conduct the damage assessment. Tools are also needed to process the collected data. These include computational machine learning algorithms, which use the raw data taken in the field and convert it into practical measures related to damage assessment for the end user (e.g., emergency manager or academic researcher). One of the most common computational tools are computer vision algorithms, which have been used to find infrastructure assets and determine damage measures [158]. Algorithms have also been used to compare pre- and post-disaster images to determine collapsed and non-collapsed buildings using aerial images [159]. Other applications include using in-the-field pictures to identify damage in reinforced concrete columns, such as cracks or component displacements [160], and automatically classify building damage in post-event reports [161,162]. These pictures can be cataloged using smartphone systems, as was done in the Nepal Earthquake in 2015 [163]. Machine learning has also been used to assess a building's structural safety after an earthquake. For instance Ref. [164], used classification, regression trees, and random forests to identify the structural safety of an earthquake-damaged building. Similar to this work, Ref. [165] found patterns in tall damaged buildings using support vector machines (SVMs), and Ref. [166] identified damaged buildings using convolutional neural networks (CNNs).

Lastly, social media is one of the newest tools used to collect and disseminate information about infrastructure damage worldwide. Images from Twitter have been used to identify the locations of building damage. With a picture of a damaged building, it is possible to generate a heatmap to identify elements in the structure with high damage [167], or classify the building to a damage state [168]. The limitation of these tools is that they rely on accurate information posted by social media users; however, they can gather information from broad areas wherever users are present. The information from these tools also has the potential to improve with time as the set of images increases and there is more data to train the algorithms that classify the buildings to a particular damage state.

7.2. Damage assessment from water hazards

In cases of flooding, damages to buildings come from multiple factors, including debris impact combined with the storm surge, scouring, and foundation erosion [169]. One approach for damage assessment is based on inferences from flood levels. This process requires three main steps: first, finding flooded areas to intersect with the building inventory; second, estimating the inundation depth at each building; and third, estimating the damage state of the building given its inundation depth.

To find flooded areas, remote sensing images have been a widely used tool. This comes from the fact that most areas are difficult to access immediately after a flood event. For example, satellite imagery has been used to find flooded areas [170,171,172]. Similar to the Damage Proxy Map released by NASA, a newer version of this product finds damage after flood events using SAR satellites [173]. Finding the flood extent is just the first step, and thus, some methodologies incorporate computer vision to estimate the damage state of buildings using the obtained flood maps [105,174]. LIDAR scans and UAVs have also been used for this purpose [175]. However, remote sensing does not provide a precise estimation of damage given the capabilities and limitations of aerial imagery, i.e., remote sensing tools are capable of providing broad observations of an area but only based on an aerial view of damage. Thus, remote aerial imagery can only be used to estimate damage at a high level (e.g., collapsed or not collapsed). To assess the level of inundation for more detailed descriptions of the damage, flood extents can be intersected with topological data. Given the current state of topographical technology, Digital Elevation Models (DEM) provide high-resolution data that can be coupled with inundation profiles of a region to estimate the level of inundation in the region [176,177]. For preliminary estimation of flood damage, these flood maps and elevations are coupled with flood-depth damage functions, which estimate the percentage of the building value that is lost depending on the level of inundation [178].

Obtaining a more detailed and comprehensive characterization of the damage to a building requires other tools and methods. One method is through field inspections conducted by experts, similar to earthquake forensic engineering, where it is possible to determine structural damages to the exterior and interior. While providing detailed damage information, this approach can take significant time. For example, this type of field reconnaissance occurred after Hurricane Katrina in 2005 [179], where engineers surveyed affected areas in New Orleans for six months. Technology has since evolved, and the time and precision of reconnaissance missions have improved. One example is the technology used by the Structural Extreme Event Reconnaissance Network (STEER), which has been deploying new tools such as vehicle-mounted cameras to improve both the precision and time of the damage assessment in hurricanes [180,181]. With increased data sharing on the internet, researchers can publish thousands of damage images for each event. In the case of Hurricane Michael in October 2018, STEER used a vehicle-mounted Applied Streetview (ASV) camera, which records 360° footage in real-time as the vehicle moves through the damaged areas [182]. Such tools significantly decrease the time it takes to collect imagery data after a disaster. Sequential pictures, such as those from ASVs, can also be used to automatically tag building damage using computer vision [183]. In the same event, STEER conducted door-to-door damage assessments with a customized Fulcrum App. This mobile application automates the workflow of the data collection process by merging the collection and publication of the datasets, generating automatic reports directly from the platform. However, the data from these tools has mainly been used by researchers rather than by emergency personnel for disaster response. Table 6 summarizes the tools available for use in damage assessment of building infrastructure.

Table 6
Summary of tools for damage assessment of building infrastructure.

Tool	Description
Seismograph	Measures critical earthquake parameters such as peak ground acceleration (PGA) and velocity (PGV) to quantify the earthquake's magnitude and intensity. These parameters are used in multiple damage assessment methodologies coupled with fragility curves.
ShakeMap	Developed by USGS, a series of maps representing multiple earthquake parameters using data from seismographs, soil models, and community surveys, which can be used to estimate building damage.
Optical satellite imagery	Overground images are used to estimate broad damages in the first couple of days after the disaster. These images are useful to estimate collapsed buildings and flooded areas.
Synthetic Aperture Radar (SAR)	Sensor mounted in satellites that generates energy signals to measure the amount that is reflected from Earth.
Field inspection	Both academic teams and public entities use structural engineering experts in the field to better determine the damage to buildings. These engineers examine the failure in the building components and establish a damage state.
LIDAR Sensors	Used to quantify component displacements in structures at a high resolution. Point clouds allow capture of a 3D model of the building.
Unmanned Aerial Vehicles (UAVs)	Equipped with cameras and/or LIDAR sensors, drones are used to better capture damages in locations with difficult access. Can also be used to automatically capture 3D images of multiple structures.
Computer vision algorithms	Machine learning tools to assess damage on buildings at different resolutions. Input data include satellite images and in-the-field images for the comparison of pre-and post-event states, and identification of damage such as cracks and damaged components in a structure.
Smartphone applications	Smartphone systems are used to catalog building pictures efficiently. This data can be assessed at later stages using a shared database.
Social media data	Both texts and images are used to identify severe damages in the aftermath of a disaster. This data is useful to identify hotspots of damage, so entities can then improve damage estimations using remote sensing or more detailed inspections.
Digital Elevation Models (DEM)	Coupled with flood maps, these datasets can be used to determine inundation depths on buildings and corresponding damage levels.
Vehicle-mounted Applied Streetview (ASV)	Camera that records 360° footage in real time through affected areas to record the route taken by reconnaissance teams. This tool can make building damage tagging faster when coupled with computer vision algorithms.

8. Discussion

While the previous section details the tools available for damage assessment in each infrastructure system, this section analyzes the availability and characteristics of tools across systems to examine the scope, limitations, and opportunities of data collection tools in post-disaster damage assessment. The analysis is divided into five subsections. First, an analysis of the availability of tools for each system. Second, a comparison of key features of the main tools, including data coverage and precision. Third, the gaps identified among the current tools and capabilities. Fourth, recommendations for improving damage assessment on buried infrastructure by increasing data sharing and leveraging their geographical interdependencies. And fifth, a discussion of the value of tool awareness for increased integration of information across datasets and potential coordinated data collection in post-disaster environments.

8.1. Availability of tools by system

From the information presented in the previous sections, several tools are used to assess damage to multiple infrastructure systems. For instance, satellite images determine early damage extents across multiple lifelines. Based on the range of tools available across

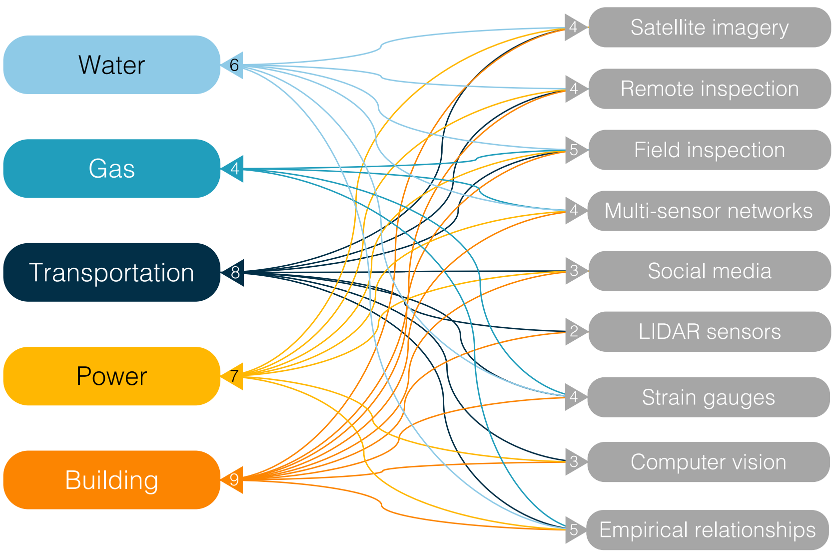

Fig. 2. Distribution of data collection tools for the five major infrastructure systems.

infrastructure systems, nine major tools are identified, as shown on the right-hand side of Fig. 2. These are connected with the five major infrastructure systems studied in this work, as shown on the left-hand side of Fig. 2. Fig. 2 illustrates the connections between each infrastructure system and the nine major tools to visualize the commonalities across tools and sectors. Some specific tools are included as part of a larger category of tools (e.g., Twitter data as part of social media data). The category labeled empirical relationships includes the tools that record post-disaster data for estimating damage through empirical models, such as leveraging the relationship between PGV recorded from seismographs and pipeline failure to assess pipeline damage, or using PGA to estimate building damage states. The number of tools used for a particular system out of the nine major tools available is shown in the arrowhead from the tools on the right leading to each system label on the left of the figure. The number of systems using each tool is shown on the right arrowheads.

The connections shown in Fig. 1 between the data collection tools used for post-disaster damage assessment and the five major infrastructure systems examined in this work show that building infrastructure has the most available tools for damage assessment. In fact, of the nine major types of tools examined in this work, building infrastructure utilizes all of them. This can result from the historic focus on these structures in damage assessment compared to other lifelines and the time and research implemented to study and improve damage assessment for buildings. The sector with the second most tools used is for transportation infrastructure, with eight out of the nine tools utilized. Thus, the two systems with the most tools available for damage assessment are both overground systems (transportation and buildings). These systems can be assessed with a more extensive set of tools compared to buried networks, which rely on underground tools and specialized remote sensing techniques. As a result, Fig. 2 also shows the lack of tools being implemented for gas networks (only four of the nine major tool types are used). How damage data collection might be improved for buried infrastructure is discussed later in this section.

In terms of tools, the most widely used are field inspections and empirical relationships, then satellite imagery, remote inspection, multi-sensor networks, and strain gauges. The widespread use of empirical relationships across systems is a testament to the research work that has been conducted in establishing these relationships and enabling damage to be inferred from other measures of disaster event intensity. Field inspections have traditionally been used from among the set of available tools because of their relative reliability and the ability to provide detailed and specific assessments of damage according to particular engineering criteria. As a result, inspections are currently used on all infrastructure systems. However, individual asset inspections take time and significant personnel resources, and thus, there has been a growth in recent years of alternative sensing and data collection methods, including using remote satellite imagery and multi-sensor networks. Among these is the use of machine learning techniques and the increased use of UAVs to make the damage assessment process more efficient and effective. It is anticipated that the use of these alternative sensing and data collection techniques will continue to increase and expand in capability for assessing damage in different infrastructure systems.

8.2. Tool comparison by key data features

Most post-disaster data tools used for damage assessment vary in coverage, precision, availability, resources required, and processing time. Fig. 3 compares the coverage, precision, and availability over time relative to the disaster event for the datasets produced by each of the nine main tools presented in section 8.1. Information about the latter two tool characteristics of monetary resources and processing time is usually unavailable in the academic literature. Thus, the focus in Fig. 3 is on the key data features of coverage, precision, and availability. Compared to the nine main data tools shown in Fig. 2, remote inspections, computer vision, and empirical relationships are divided into more specific tools in Fig. 3, as these subcategories differ in terms of data precision and time of availability. Remote inspections are divided into three subcategories: those from internal inspections of pipelines for buried infrastructure,

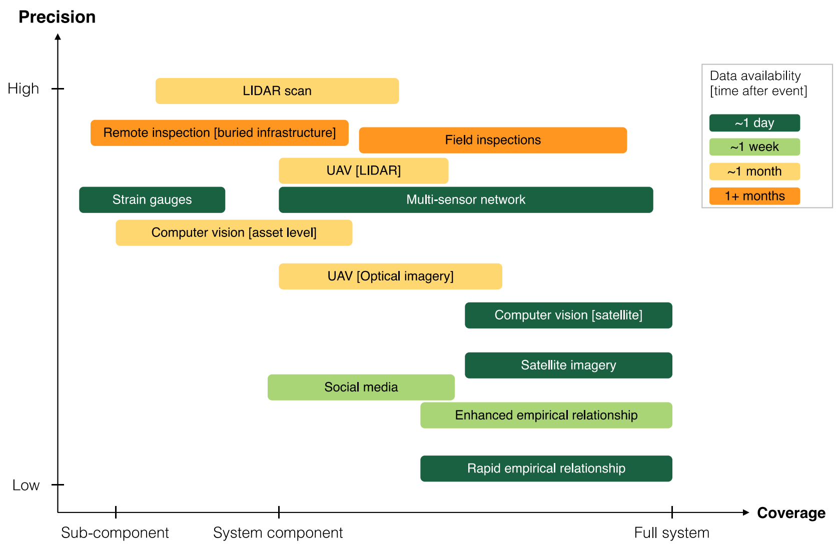

Fig. 3. Damage assessment tool comparison in terms of coverage, precision, and data availability.

those using UAVs with LIDAR sensors, and those with UAVs equipped with conventional cameras to collect optical imagery data. Computer vision is divided into two subcategories depending on if the data source comes from satellite imagery or asset-level field inspection pictures. Finally, empirical relationships are divided into two subcategories: the ones that are rapidly released within the first day of the event, which rely on uncertain data, and those that integrate multiple sources of data to enhance damage estimation.

In Fig. 3, coverage ranges over three levels of coverage as shown on the horizontal axis. First, the sub-component level (e.g., a column of a building or pipeline section). Second, the system component (e.g., power substation, single building, transportation road). Third, the entire system (e.g., transportation network, complete building inventory). In terms of precision, each main tool ranges from low to high, as shown on the vertical axis. Precision includes the physical resolution of the tool (how fine the collected data is, e.g., sub-cm for LIDAR scans or 30 m for early satellite imagery) and the reliability of the tool (how likely the tool is to be accurately measuring the damage, e.g., satellite imagery has low reliability to estimate buried infrastructure damage, while expert inspections have high reliability on individual building damage). With these specifications, rapid empirical relationship, for example, is shown as the tool with the least precision for infrastructure damage assessment because it relies on uncertain data that is not directly measuring damage, such as ground motion or water depth. In contrast, LIDAR scans provide the highest precision because they allow the viewing of a structure in a 3D model at high resolution.

The distribution of data availability over time in Fig. 3, represented by color, shows that 5 out of the 13 tools are used one day after the event. Excluding strain gauges, which produce damage data on specific components, these tools have extensive coverage, resulting from the need for rapid initial estimations of the damage across an entire affected region. Thus, covering large areas in a short time requires tools that capture information rapidly at the expense of precision. Thus, damage data from rapid empirical relationships and satellite-based tools have low precision. For example, the resolution of ground motions in the ShakeMap is 1000 m [184], which is useful for understanding the distribution of the impact of the earthquake, but not enough for quantifying damage with high precision. Similarly, the resolution of the satellite that captures Nighttime Lights (NTL) is 500 m [134]. This information can be used for locating power outage areas but not specific buildings that lost power.

In contrast, two early datasets with high precision are data from strain gauges and multi-sensor networks. This shows the value of these tools and motivates their increased use for damage assessment to provide both rapid and high-precision information. However, a critical consideration for using these tools in post-disaster contexts is their power and communication requirements and their dependence on the operation of these networks to collect and communicate their data streams to users during and after a disaster occurs.

Compared among the remote sensing techniques used in damage assessment, LIDAR scans provide data with the highest precision because it produces 3D scans of a structure, allowing users to view multiple angles of a structure. Given the detailed data collected, however, coverage is relatively low. UAVs with LIDAR sensors have less precision given that scans are taken at a farther distance than conventional LIDAR scans, but they can cover a larger area. UAVs with conventional optical imagery cameras can cover larger areas than with LIDAR scans, at the expense of precision, given that the resulting images are in 2D and not 3D.

For data from inspections, both remote and field inspections on infrastructure systems have high precision but results from this data collection tend to be available months after the event. This long time to data publication comes from the fact that such detailed infrastructure damage data is often not essential to immediate rescue and recovery activities and thus is not prioritized compared to emergency tasks. They are essential, however, in applications for federal aid to support longer-term recovery efforts, and thus data from these tools become available in the 1+ month after the event. In terms of coverage, field inspections usually eventually cover a large part of the affected area once they are completed but will not cover an entire area, given that most reconnaissance missions focus on areas with high damage.

Finally, social media tools and empirical relationships produce data that can reach high coverage at the expense of uncertainty. Therefore, both tools have relatively low precision. Improved technologies can enhance the reliability of social media tools. However, technology has not reached a level for it to be consistently used for damage assessment during the response to a disaster. Rapid empirical relationships are used for post-disaster assessments that do not require high precision data, such as estimating overall losses and economic impacts to an area after an earthquake [185,186]. The precision of these estimates improves throughout the disaster response period, with additional data continually being collected, to update these estimates with higher precision through enhanced empirical relationships.

8.3. Gaps in data collection tools

The analysis from Figs. 2 and 3 reveals gaps in current data collection tools for assessing post-disaster damage. As shown by the availability of tools in Fig. 2, buried infrastructure systems, including gas networks, water distribution systems, and some power networks, are behind other infrastructure systems regarding the availability of damage assessment tools. With the criticality of water and power for human health and gas to supply essential needs such as heating, this gap in data tools means that understanding the specific damages to these systems takes longer, lengthening repair and recovery times, and negatively impacting community resilience. For this reason, there needs to be increased development and implementation of technologies that improve the damage data collection process for these networks. In power networks, for example, new technologies such as smart grids and wide area monitoring can improve situational awareness for emergency managers [187]. In the case of water distribution systems, wireless sensor networks have proven effective in reducing the time of data collection [32]. These implementations are critical for improving the assessment of buried infrastructure.

In addition to the lack of tools, current devices for assessing detailed damage in buried networks are expensive and time consuming. Instruments like CCTV robots or fiber optic sensors are costly and require personnel to be physically present to assess a single component. Moreover, these devices are usually developed by specialized companies that can charge high rates for their products, given their unique ability to supply these products and services. On the other side of the spectrum in terms of the precision of data collection tools, methodologies that estimate damage at a large scale (e.g., methods that utilize social media or satellite images) are highly uncertain. For example, even though there is potential for implementing social media information as a proxy for network damage [188], their implementation by utility providers is not yet standardized and useful for recovery purposes. Further discussion about specific recommendations for improving data collection on buried infrastructure through increasing data sharing and leveraging geographical interdependencies is provided in the following section.

In assessing gaps in data collection tools, the analysis from Fig. 3 also shows that across sectors, no tool provides data with high coverage and high precision for damage assessment, particularly if data is desired quickly after an event occurs. The closest two are field inspections and multi-sensor networks. For field inspections, they are costly and time consuming, requiring personnel training before an event and a significant investment of time and resources after the event for data collection. Collected data is also subject to potential biases across individual inspectors. For multi-sensor networks, tools of this type are still in development and require widespread instrumentation to be installed before the event to be effectively utilized. In order for this tool to be widely implemented across multiple infrastructure networks, ongoing challenges about power supply of the sensors, large-scale data collection, and sensor durability need to be addressed [62,63]. This leaves room for research to enhance these technologies to improve not only the monitoring of infrastructure but also the effectiveness of using these datasets for post-disaster damage assessment.

8.4. Improving data collection on buried infrastructure through increasing data sharing and leveraging geographical interdependencies

One of the challenges with collecting data on damages to buried infrastructure, such as water distribution systems, gas networks, and some power networks, is that such damage data is not usually publicly available. For data from tools currently implemented for monitoring, the data flow rarely goes outside utility providers, making damage data on these systems more private than for other infrastructure sectors such as transportation and buildings. Emergency managers should advocate for minimum data-sharing recommendations (see Ref. [189]) in order to promote publicly available data on the status of buried infrastructure assets. This information is critical for entities that require the allocation of resources and the consideration of interdependencies of these networks, e.g., the use of water, power, or gas resources for recovery. For example, utility providers could share data about areas of high impact without compromising specific private data. This information would help emergency managers to decide where to perform comprehensive damage assessment (i.e., with high precision) and where to locate points of resource distribution.

For utility providers that do not have the resources to implement widespread monitoring in their networks before a disaster occurs, one way to overcome the extensive effort required to assess damage in buried infrastructure is by coordinating data collection locations across providers. This way, both the coverage and precision across the buried infrastructure networks would increase. This is possible due to the geographical interdependencies of many lifeline systems [71,190]. A large percentage of the networks are constructed close to each other in urban areas. While there are limited technologies that can locate all underground utility services with high precision and can be generally applied in practice [191,192], increasing coordination and data sharing across utility providers and infrastructure owners would facilitate more efficient and less expensive damage data collection, e.g., by just digging once to assess and repair damage.

To effectively leverage geographical interdependencies for damage assessment of buried infrastructure, several challenges need to be addressed. The first is that doing so will require an effort to map old and new lifelines in order to prioritize data collection areas. In the meantime, non-invasive tools such as ultrasonic sensors can be used to assess the status of multiple networks simultaneously. The second is a concern for data privacy and security. In that case, the data stream could occur solely between the utility providers. Third is arranging cost sharing. Coordinating data collection and sharing the data across providers can potentially reduce damage assessment costs since the inspection costs can be shared. For this to happen, these stipulations need to be agreed upon before the disaster to avoid legal obstacles. Even with these challenges, there is the opportunity to leverage the geographic proximity between networks to generate a collaborative process between utility providers so that in cases where the networks coincide, the post-disaster data collection process can be more efficient (taking less time and resources to collect data) and effective (collecting information about more assets across the network).

8.5. The value of tool awareness for integrating datasets across tools and increasing coordinated data collection

With the range of tools available to collect information on post-disaster damage of infrastructure, knowing the characteristics of the tool used to collect a post-disaster dataset facilitates the integration of information from datasets across tools. Specifically, this paper

Table 7
Comparison of dataset features and the impact of tool awareness.

Data Feature	Dataset 1 Reconnaissance team	Dataset 2 Pre- and post-event satellite images	Impact of tool awareness
Resolution	High. Detailed building photographs	High. 1 m by 1 m pixels	Detailed description of data limitations and uncertainty.
Precision	High. Experts have ability to view multiple aspects and locations of damage.	Low. Satellite only allows one view of the damage.	Improved ability to assess multiple types of damage and improved data reliability for loss analysis (e.g., economic impact, casualty rates).
Coverage	Buildings around reconnaissance route	Complete region	Allows damage assessments of additional buildings to be inferred.
Processing time	2 weeks	1 day	Provides minimum time required to acquire a dataset and its connection with emergency tasks.

demonstrates that certain tools are more tailored for certain stages of the disaster response. For instance, drone imagery is useful to rapidly assess large regions. Strain gauge instrumentation is useful to provide detailed damage data on specific parts of a system. In this way, a dataset should always include the tool used for collection in the metadata to improve the post-disaster data collection process.

When sharing a damage assessment dataset, it is not common to publish details about the tool used to collect the data. For instance, a study of data from two disaster events in Puerto Rico found that 42% of the datasets did not publish the specific tool used in the field [193]. Most datasets are published along with metadata features such as time of publication and coordinates of collected data. Even though these features are important, not knowing specifics about a given data collection tool can increase uncertainty during the analysis of the data and in converting the collected data into assessments of damage .

With a clear understanding of the tool, a user can better interpret four critical dataset features: resolution, precision, coverage, and processing time. The value of this improvement–increasing tool awareness– for damage assessment is demonstrated by comparing two datasets that look the same when the tool is unknown but result in clear differences for damage assessment when details about the tool are known. Imagine two point datasets that represent damage classification of buildings. Each dataset has a list of buildings with their respective estimated damage state (e.g., moderate, extensive). At first, both datasets look the same. However, the first dataset was collected by experienced reconnaissance teams who were in the field, and the second was produced using an algorithm that compares pre- and post-event satellite images. Table 7 summarizes the differences between the two approaches and the impact of tool awareness on assessments of data resolution, precision, coverage, and processing time.

As seen in Table 7, the resolution of both datasets is high because each tool estimates damage per building, not block or neighborhood. However, both the resolution and precision of dataset 1 are higher because reconnaissance teams can observe each building from multiple angles rather than just the aerial view of dataset 2. This advantage results in a more detailed description of the damage and higher reliability for disaster impact analysis.

The two datasets also vary in terms of data coverage. In dataset 1, for example, the extent of assessed buildings depends on the route taken by reconnaissance teams. Due to time restrictions, it is difficult for these teams to cover all buildings in a city. This restriction results in incomplete coverage of the building inventory and the impossibility of knowing if the buildings for which data was not recorded, i.e., untagged buildings, were the result of them having no damage or if data were simply not recorded for those buildings. On the contrary, for dataset 2, most satellites can take images of 30 km by 30 km, covering most large cities in the world. Therefore, at the expense of precision, satellite images can provide complete coverage of the damage compared to detailed descriptions from experts in the field covering a portion of the region.

Finally, information about the tool also provides a proxy for the processing time required to publish a dataset. This information is helpful in cases where time stamps are not provided because it lets emergency managers and other disaster responders know what type of data to expect at different stages of the post-disaster response. As a result, with few additional resources required (only to know and report the type of tool) the publication of the tool in the metadata of a dataset not only improves knowledge about the technical features of a dataset but also provides information about the dynamics of data availability for damage assessment and recovery planning.

Increased tool awareness supports improved coordinated data collection in the post-disaster period, such as using specific tools to fill gaps in knowledge of the disaster impacts across infrastructure systems. Understanding the characteristics of the specific tool in a dataset provides critical information for the development of new data processing methodologies. For example, multiple datasets can be used together if their features help to improve damage assessment. Satellite imagery (of low precision) can be coupled with in-the-field assessments (of high precision) to expand the extent of analysis, considering the availability of satellites and the time needed for tagging buildings and processing field surveys. Implementing this integration would require developing new processing methodologies for data fusion in order to produce consistent outputs of damage across datasets that include the integrated uncertainty of both datasets.

9. Conclusions

Determining the damage extent on infrastructure systems is a critical task for effective emergency management and infrastructure recovery. The interest in improving the assessment of these systems has increased the number of tools available and applied in the field for post-disaster data collection. This paper describes the state of the art of damage assessment in lifeline and building infrastructure. Five major infrastructure systems are considered in this work, including water supply, gas, transportation, power, and buildings. A comprehensive review of the tools used for each system is presented, covering two types of hazards: earthquakes and water hazards. Among these tools, nine major tool types are identified: satellite imagery, remote inspection, field inspection, multi-sensor networks, social media, LIDAR sensors, strain gauges, computer vision, and empirical relationships.

Along with the description of specific data tools, this paper analyses the availability of tools per system and compares the main tools in terms of coverage, precision, and time of availability after the disaster. Based on this analysis, we identify and describe the gaps in damage assessment on infrastructure systems, particularly that while there are emerging tools available to provide broad coverage of an area, there is a lack of tools that are rapidly available after a disaster event that provide data with high precision. In terms of assessing the set of five infrastructure systems studied in this work, we also observe a fewer number of tools available for water, gas, and power networks (compared to transportation and building infrastructure), highlighting the need to improve damage assessment on buried infrastructure. With the lack of publicly available data for these lifeline systems, we recommend improving data collection on buried infrastructure through increased data sharing. We also propose leveraging the locations where these networks share underground space, i.e., geographic interdependencies, to support coordinated damage assessment by collecting data for multiple systems simultaneously. This approach would reduce the time to inspect underground lifelines and improve the shareability of data among utility providers.

Furthermore, we discuss the importance of including information about the specific tool used for data collection in the metadata of every post-disaster dataset. This information facilitates understanding not only the dataset's limitations (such as its resolution and coverage) but also its reliability and processing time for analysis. An example of two datasets obtained using different tools provides evidence of the importance of including these features. Increased tool awareness provides a basis for integrating information from datasets across tools and the possibility of increasing coordinated data collection to improve the understanding of damage across a community and across infrastructure systems in post-disaster contexts.

Declaration of competing interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

Data availability

No data was used for the research described in the article.

Acknowledgments

This work was supported by the National Institute of Standards and Technology under Award #70NANB19H062.

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